PART 4: SOCIAL CHALLENGES OF AI

17. From AI Bias to AI By Us: A Case Study from MIT Critical Data

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Abstract. This paper advocates for inclusive AI development, emphasizing its necessity for global equity, ethical soundness, and social relevance. We detail MIT Critical Data's approach to equitable AI development, focusing on healthcare. Our methods prioritize diverse collaboration and community engagement. Through global datathons, open-source datasets, and accessible education, we empower the global majority to actively participate in shaping AI that benefits all. Significant results, including numerous publications and established community hubs, demonstrate the impact of this approach. We argue that inclusivity in AI is not only achievable but crucial for its future success and fairness, particularly in serving the global majority.

Introduction

The Importance of AI from the Global Majority

While artificial intelligence (AI) influences society globally, its development and deployment are concentrated in technologically and economically dominant regions, leaving the majority of the global population underrepresented (World Health Organization, 2024). This disparity results in AI systems that do not reflect the diversity of the global majority. Consequently, these systems may perpetuate and exacerbate biases and inequities, further marginalizing already vulnerable populations (Shaffer, Alenichev, & Faure, 2023). The potential for AI to drive positive change is immense, but only if it is developed responsibly through a process that is participatory, inclusive, reflexive and reflective.

Inclusivity in AI development is not only a matter of equity, but is essential for any system that is ethically sound, socially relevant, and economically beneficial to all (Hendl & Shukla, 2024; Jansky, Hendl, & Nocanda, 2024). By involving diverse voices in the AI creation process we, as a society, can ensure that these technologies are reflective of and responsive to the varied experiences and needs of different populations. At MIT Critical Data, we have taken these challenges head-on by employing a grassroots, local-first approach that prioritizes diversity and inclusivity in AI development. Through our initiatives, we aim to build a more equitable AI landscape that benefits everyone, not just a privileged few. This paper highlights our methods and the tangible outcomes of our work, demonstrating how inclusivity in AI is not only possible but essential for the technology's future success and fairness.

MIT Critical Data's Approach to Achieving Equitable Development, Transparency, and Accountability for AI

At MIT Critical Data, we recognize that engaging diverse communities is essential to combating bias in healthcare AI. Our approach is derived from five distinct core values: (1)rigorous and innovative research, (2)multi-level and accessible teaching, (3)building and networking communities of primary stakeholders, (4)reimagining legacy systems of power, and (5)advocacy for epistemic humility and health equity. We strive to unite the full range of professional, empirical, and cognitive backgrounds to foster collaborative imagination.

17.1. Discussion

17.1.1. Pioneering Research Methods in Healthcare AI

We conduct our research under the premise that AI has both the capacity to revolutionize healthcare, and to harm it. It is clear that relying solely on model prediction accuracy as the final arbiter for its implementation is short-sighted, not generalizable, and risks significant harm to populations traditionally excluded from research and model training (Futoma, Simons, Panch, Doshi-Velez, & Celi, 2020). Rather than merely developing highly accurate models using robust methodologies, we prioritize addressing foundational challenges in machine learning for healthcare and incorporating any model development into the broader context of the data. Recognizing the many biases inherent to healthcare AI across all stages of the pipeline (Gichoya et al., 2023), we have made efforts to create guidelines for responsible AI development, such as a well-validated checklist called TRIPOD-LLM (Gallifant et al., 2024). This specific tool helps quantify the severity of bias in published studies using LLM models, and also serves as a framework for responsibly designing prospective healthcare LLM studies. Key considerations for responsible AI development include identifying and involving community members who would be most impacted by it, collaborating with co-authors from diverse backgrounds, openly discussing conflicts of interest, deeply understanding the data's story and fidelity, mitigating "hidden signals" in the data (Gichoya et al., 2023), and committing to the replicability of digital research through open science (Seastedt et al., 2022; Watson et al., 2023).

Nevertheless, it is important to underscore that AI research transcends any single cognitive or organizational domain and should not be developed, appraised, or regulated in a vacuum. Given its vast applicability, as we see, there are no individual experts in AI, only collective wisdom. For that reason, our research ranges widely, including large language models, AI model error interrogation, causal reinforcement learning, scientometric analysis, network science, epistemic research, time-series deep learning of electronic medical record data, ethics, vector embeddings, and implementation science. As such, to ensure a holistic approach, we collaborate globally with a diverse array of experts including social scientists, computer engineers, network scientists, ethicists, philosophers, physicians, veterinarians, pharmacists, data scientists, and statisticians. We believe that healthcare AI research should be cultivated within the global majority through a crowd-sourced approach that bridges communities and disciplines, and advances the decentralization and democratization -inclusion- of health equity research. This mission is furthered by teaching knowledge and skills, empowering others to pass this understanding forward.

17.1.2. Multi-level and Accessible Teaching

To nurture collaboration, one of our focuses is on teaching. Our approach includes a wide range of training, education, expertise, age groups, and demographics. We partner with local and distant high schools and community colleges to advance healthcare AI education, sharing model development coding notebooks, providing access to open data sets, and offering tools to assess expected bias and harm. Our lab hosts a rotating cohort of visiting students from all over the world. We also teach at the Harvard School of Public Health, MIT, offer a freely available edX course, involve medical residents at Beth Israel Deaconess Medical Center, and engage in many more educational venues. We then translate this approach to durable, community-focused educational initiatives, particularly through global datathons, as discussed below.

17.1.3. Investment and Networking of Relevant Communities

As discussed, AI in healthcare cannot succeed without recentering the global majority to the forefront. To collaborate towards that goal, our approach centers on elevating primary actors involved in AI model development by initiatives such as incorporating their perspective into the TRIPOD-LLM bias assessment tool and validating a team scorecard applicable to any healthcare AI project. Also, we work to establish community hubs –organically scaled networks that bring together people from neighboring countries and regions. These hubs serve as grassroots initiatives, fostering a community of individuals committed to advancing equitable AI. By building those networks, we ensure to connect and empower the capacity that is mostly already present within the communities. Furthermore, at the local level, we nurture the next generation of AI leaders, equipping them with the critical perspectives needed to challenge prevailing biases in healthcare datasets. Our ethos is that critical thinking cannot thrive in a room where everyone thinks the same way. We believe that diversity in thought and experience is key to developing AI that is truly inclusive and effective.

One of our main drivers to establish such networks is through a global network of datathons and policy camps (Aboab et al., 2016). Our datathons are immersive, multi-day events held in countries across the globe. These events provide spaces where interdisciplinary teams can critically engage with open health datasets as well as collaborate to uncover and address biases that could influence AI models, ensuring that these technologies prioritize health equity. Those are not only confined to capital cities; they are also hosted in smaller towns and regions that are often overlooked in global initiatives. This approach allows engagement of talented individuals from various backgrounds, ensuring that the AI solutions reflect the communities they are designed to serve. Furthermore, datathons and policy camps are often conducted in local languages, enabling participants to communicate and collaborate effectively, regardless of their linguistic backgrounds.

17.1.4. Reimagine Legacy Systems of Power and Expertise

When it comes to reimagining legacy systems, we stand for the decentralization of medical knowledge and the democratization of clinical data sharing. To achieve this we advocate for alternative metrics beyond the traditional impact factor to evaluate the impact of scientific journals, promote open access, and support open science to maximize scientific replicability. Our focus on data which is Findable Accessible Interoperable and Reusable (FAIR) reflects our dedication to transparency (Jacobsen et al., 2020). Moreover, aiming to diminish the barriers of data gate-keeping, we host PhysioNet, a continually-building collection of 314 large physiological and clinical datasets (at time of writing), over 50 related open-source software packages, and over 30 tutorials and reference guides. Among these datasets is the well-known Medical Information Mart for Intensive Care (MIMIC) now in its fourth iteration (MIMIC-IV), which includes data on 12,881 patients and 13,941 ICU stays from 2010-2018. Branches of this data set include raw CXR images, ECG waveforms, echocardiograms, emergency department encounters, and free-text clinical notes for large language models. All code is freely available and access is regulated through a data use agreement. As a result, preliminary data shows that MIMIC datasets are cited significantly more often than several proprietary publicly available datasets, with citation numbers ranging from 48.8-2,523.7 times higher, an advantage that grows further when adjusting for funding received.

17.1.5. Advocacy for Epistemic Humility and Digital Health Equity

Developing responsible AI in healthcare requires recognizing that this is a complex and multifaceted problem. Moreover, several common principles should be generally understood. First and foremost, when it comes to regulation, the authority to create policies around these systems must be primarily informed by those most affected. That is, when legitimized decision makers, such as regulatory agencies, are designing policies around AI, they should consult with the most affected stakeholders. For instance, if a healthcare AI model is to be trained and applied to people with HIV in South Africa, then people with HIV in South Africa must have a seat at the table for every stage of its development. Secondly, well-defined transparency standards throughout the AI model's lifecycle –from the conceptualization to implementation– must be developed. Third, rather than evaluate the AI bias of a model *post-hoc*, there may be value in mandating a prospective, systematic evaluation. However, it is important to emphasize that this is not a comprehensive list, and further initiatives are part of the iterative process towards building fairer outcomes for AI in healthcare.

As an example of future explorations towards responsible AI development, we are currently developing model interrogation tools to identify groups that might be harmed by false negative and positive predictions during the model validation stage. More classic approaches towards model performance evaluation are often insufficient, as shown by numerous studies that have identified "accurate" models in training and testing stages using conventional performance metrics, yet these models have ultimately caused harm or contributed to patient mortality when applied in real-world settings (McDermott, Hansen, Zhang, Angelotti, & Gallifant, 2024). While we have suggested some alternatives (Gallifant et al., 2023), these are still under development.

This is an iterative process, many times constrained by our collective imagination, and potential is lost when we surround ourselves with people who think exactly as we do. To counter this, we also created symposia for epistemic humility and critical thinking where individuals from any discipline can come together to discuss the broader ethical, regulatory, and societal implications of AI in healthcare. Through those, we have learned that before regulation of AI health equity among the global majority can be more fully addressed, there are clear structural and systemic challenges to engage. We need to continue developing AI error interrogation tools and alternative performance metrics that capture the humanity inherent to the data. It is essential to incentivize peer-reviewed journals to reject manuscripts which only report accuracy of yet another new AI model. Educated community actors in AI must be involved in policy-making and. We must advocate for making science and data accessible from behind paywalls and ensuring it is understandable to those without the privilege of academic immersion. Collaboration in all forms, across disciplines, cognitive domains, cultures, religions, quantities of education, race/ethnicity, industries, and nations is essential to fully open the gates keeping AI from the global majority.

17.1.6. Results and Impact of MIT Critical Data's Approach

Our results have been significant, both in terms of academic output and real-world impact. Since 2014 we have hosted 46 datathons in 21 unique countries, including Singapore, Taiwan, the Philippines, Mexico, and more. Over 2,000 publications have been produced and a formal network effect assessment is also underway. These papers not only advance the field of healthcare AI but also ensure that contributions come from a broad spectrum of voices, particularly those from the underrepresented global majority. There are over 9,000 citations from over 40,000 people using the over 300 open-source datasets hosted on the PhysioNet Platform. These citations reflect the widespread adoption and influence of the datasets we maintain, which are used by researchers globally to develop AI solutions. Importantly, many of these citations come from researchers affiliated with low- and middle-income countries (LMICs) and minority-serving institutions (MSIs) in the United States, highlighting our success in promoting greater authorship representation from these regions.

Furthermore, the establishment of critical hubs has played a pivotal role in our initiative's success. By creating organically scaled networks that connect people across neighboring countries, we have fostered a sustainable and resilient community of AI practitioners. These hubs are not reliant on external funding guarantees but are instead driven by the shared commitment of their members to advance equitable AI. For instance, AI. For instance, the collaboration between Mbarara University of Science and Technology (MUST) in Uganda and MIT exemplifies the transformative potential of these hubs. Rogers Mwavu, a computer scientist from Uganda and one of the key leaders in building this alliance, describes its impact:

"The MUST-MIT collaboration has significantly advanced a multidisciplinary approach to improving global health in Uganda, addressing key challenges such as maternal health, HIV/AIDS, and non-communicable diseases," Mwavu explains. This partnership has been particularly impactful in building local capacity and developing sustainable, culturally relevant solutions. By combining MIT's technological expertise with MUST's local insights, the collaboration has equipped healthcare workers, students, computer scientists, and community leaders with skills in data collection, analysis, and application. As a result of this long-term collaboration, researchers at MUST have implemented mobile-health tools for real-time patient data collection in remote areas, utilized telemedicine for expanded access to specialized care, and leveraged big data analytics to track health trends and predict disease outbreaks. This mutually beneficial partnership has not only enhanced healthcare delivery and research capabilities in Uganda but has also provided MIT students and faculty with valuable experience in applying technology to global health challenges, further demonstrating the reciprocal nature of our hub model.

Further concrete outcomes of our approach are reflected in the high-impact publications that have emerged from our initiatives (Collins et al., 2024; Ellen et al., 2024; Gottesman et al., 2019; Gottlieb, Ziegler, Morley, Rush, & Celi, 2022; Komorowski, Celi, Badawi, Gordon, & Faisal, 2018; Wong et al., 2021; Wu et al., 2022). These publications are not just a measure of academic success; they represent real-world advances in how AI can be used to improve healthcare for diverse populations. By involving diverse stakeholders in the co-creation process, we have developed AI solutions that are not only technically robust but also aligned with the needs and realities of the communities they are designed to serve.

CONCLUSION: LESSONS LEARNED AND FUTURE DIRECTIONS

Through our work at MIT Critical Data, we have demonstrated that inclusivity in AI development is not only achievable but also essential for creating equitable healthcare solutions. Some challenges have included both ensuring sustained engagement from participants in underrepresented regions and bridging the gap between diverse linguistic and cultural contexts. We continually adapt our methods to ensure that our initiatives remain accessible and relevant. The need for sustained engagement underscores the importance of building long-term relationships with local communities, rather than relying on one-time events. Similarly, the diversity of linguistic and cultural contexts enriches the AI solutions developed through our initiatives, as they are informed by a broader range of perspectives and experiences.

As we look to the future, we urge the global AI community to recognize the value of engaging with diverse populations and to make a concerted effort to include voices from the global majority in AI decision-making processes. The future of AI in healthcare depends on our collective ability to build systems that are not only technologically advanced but also equitable and just. Together, we can create an AI landscape where every voice is heard, and every community benefits.

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18. THE PROSUMER IN AI GOVERNANCE: CLASS ANTAGONISMS AND THE SOCIAL RELATIONS OF LABOR

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Abstract
This paper examines "data prosumer" as an ideological construct essential to contemporary capitalism, framing users as virtual data producers who leverage personal data to assert privacy rights and engage in market activities. This abstraction helps commodify social interactions, reducing diverse human activities to exchangeable data units.
While personal data is governed by individual rights, non-personal data is appropriated by governments to create data markets that support visions of digital sovereignty in the global economy. The paper explores the reduction of labor to data prosumers in AI governance, emphasizing how digital labor markets exacerbate socio-political inequalities and informal labor conditions, especially across the Global Majority.
It critiques the global political economy's reification of individuals as "data populations" and reintroduces class analysis to challenge data commodification amid generative AI's mystification of labor. Finally, it argues that the push for digital sovereignty through data ownership obscures the exploitation inherent in capitalist, data-driven expansion.
Keywords: Prosumer, Digital Justice, Data Rights, Labor, Workerism, AI Governance, Data Sharing, Data Value

INTRODUCTION

In the AI-driven era, the "prosumer" concept, initially developed by Alvin Toffler (1991) and George Ritzer (2019), describes individuals who both produce and consume, creating surplus value (Fuchs, 2012). I reinterpret this concept to emphasize the consumptive nature of digital social production under capitalism, where platforms abstract individuals into data values—whether as citizens, laborers, or consumers—interpellating them as a "data resource" to be reclaimed through "data ownership." This paper examines the transformation of global populations into data prosumers and explores its socio-economic implications for labor, using India's policy framework and debates on digital sovereignty and AI governance as key examples.

18.1. DUAL NATURE OF PROSUMER ENGAGEMENT

As concerns about AI displacing human labor grow, there is increasing advocacy for individuals to reclaim ownership of their generated data (Oliver and O'Neil, 2015). This perspective treats personal data as a compensatory asset (Birch, 2017; 2020), suggesting that ownership could help mitigate labor precarity.

The World Economic Forum even labels digital personal data as a "new asset class," offering potential for economic and societal value creation (WEF, 2011: 5, quoted in Birch, 2020). However, this view often overlooks the exploitative dynamics within the capitalist data economy, where human activity is commodified.

Framing data ownership as a solution to labor precarity diverts attention from the systemic inequalities exacerbated by AI. Everyday activities generate data that trains AI models and sustains the attention economy (Ricardo et al., 2022). This shift transforms users into "prosumers," whose labor, creativity, and knowledge become vital inputs for generative AI.

Data-driven societies rely on both traditional labor and emerging niche markets, where data producers meet algorithmically driven demands. This creates a paradox: while prosumer activities may seem unproductive, they are essential to the expansion of data markets.

As individuals interact with AI and the Internet of Things (IoT), the boundary between consumer and producer blurs, resulting in "data prosumption"—a form of labor critical to value creation in digital markets, yet often overlooked. Interoperable systems create digital "playgrounds" (Sukumar, 2021), seamlessly embedding data extraction into everyday life.

Platforms turn prosumer engagement into essential labor for the attention economy, while promoting the narrative that data is a form of property that the "new precariat class" (Standing, 2014) can reclaim. However, this narrative obscures the deeper capitalist logic that drives data exploitation, preventing meaningful efforts to address growing inequalities in the digital economy.

18.2. Illusion of Data Ownership

The transition from productive labor to abstract data generation has led to two significant abstractions: reducing social interactions to quantifiable metrics and fetishizing data as a commodity. Although data ownership is often presented as a route to worker liberation, platforms increasingly exploit social relations and commodify labor, exacerbating class disparities. This exploitation is especially pronounced in the Global South, where AI development relies on vast quantities of data, often referred to as the "new oil."

The capitalist division of labor, historically measured by labor time, now manifests in prosumerism and AI economies. Capitalist strategies extend working hours to extract absolute surplus value and increase efficiency to extract relative surplus value (Marx, 1867). As a result, labor that does not produce immediate data outputs is marginalized, with "unpaid labor" being redefined through data value distribution strategies (Varoufakis, 2023).

The "prosumer ideology" obscures economic inequalities by promoting data dividends through the notion of "productive consumption" (Arvidsson, 2013) on platforms that promote "socially responsible capitalism." This ideology also encourages post-work entrepreneurialism (Webster & Dor, 2023), undermining traditional wage-labor contracts.

The valorization of digital consumption as “unpaid labor” (Fuchs, 2012) creates a paradox: passive data generation is seen as productive, overshadowing the material labor that sustains the digital economy. This disproportionately affects economies in the Global South, where critical but invisible work—such as data labeling, content moderation, and gig labor—supports AI systems but is devalued in market assessments in favor of "user-generated data" as a key commodity (Gao et al., 2021).

Despite their essential roles, workers from the Global Majority remain marginalized, while wealth generated by AI accumulates in Global North platforms (Birhane, 2024). Claims of democratized access in the platform economy—where all individuals have equal opportunities as "data bodies" (Gurumurthy & Chami, 2021; Singh, 2019)—overlook how labor is restructured across industries, focusing too heavily on unequal data production value.

The narrative of egalitarian access conceals class conflicts, global labor divisions, and the precarity of workers sustaining networked publics. Celebrating digital access as "democratization" obscures the exploitation inherent in the platform economy, making systemic inequalities invisible. The idea of a digital "playground" (Scholz, 2013) for self-expression masks value extraction mechanisms, reinforcing myths of equal opportunity and ignoring persistent structural barriers.

18.3. DIALECTICS OF LABOR AND VALUE IN THE DIGITAL ECONOMY

Digital platforms are designed to capture user attention and engagement, converting historical data into user profiles and economic value. This dynamic creates tensions in AI-driven economies, where consumption often overshadows the productive labor required to maintain these systems. As data use expands, critical issues arise around ownership, rights, and labor, particularly concerning the protection of personal data and governance of anonymized and non-personal data (Gupta & Naithani, 2023).

Government interventions in data sharing, ostensibly promoting innovation by breaking data silos, often entrench exploitative labor practices. Such interventions render specific work invisible while giving data businesses access to centralized public databases. For instance, the Indian government portrays itself as both a guardian of public interest and a market architect, reshaping data to serve its "digital sovereignty" aspirations (Athique, 2019: 77). This dual role supports a broader shift towards a digital economy, especially in the Global South.

Despite the reliance on user-generated data for platforms, the labor underpinning these ecosystems—such as gig work, logistics, and data services (Dzieza, 2023)—remains undervalued. Workers are obscured within the value chain as platforms prioritize data commodification, reducing individuals to "data bodies" capable of asserting "data sovereignty" only through consent-based exchange.

India's "health stack," for example, aims to unify healthcare services by treating anonymized health data as a public good (Barlett et al., 2024; Gurumurthy & Chami, 2022, Parsheera 2024). However, the state's custodianship of data under the guise of "national public interest" paradoxically promotes data business growth while exempting certain processors from regulatory oversight to create "national champions" (Athique & Kumar, 2022; Panday, 2021).

Efforts to reclassify data based on its purpose, origin, and domain of production lack comprehensive legal clarity. Non-personal data (NPD) (Singh 2019), which cannot be directly linked to an individual's identity, often comes from "unseen workers" like content moderators, data labelers and gig workers. These workers are essential for generating and maintaining vast amounts of NPD, particularly in the Global South, where digital labor pools support multinational tech companies (Shahid, 2024; Mehrotra, 2022).

An example of how NPD is utilized in platform capitalism is real-time traffic data, often collected from gig workers such as ride-hailing drivers or food delivery couriers. This NPD enhances operational efficiencies for platforms by optimizing routes, predicting demand, and reducing delivery times.

Unlike personal data, which is often framed as empowering individuals with privacy or control, NPD is treated as a public resource that companies and governments can expropriate. This reveals the limitations of prosumer ideology, which suggests shared agency, but in reality, NPD (Verma & Gurtoo, 2021) is harvested without workers' knowledge or compensation, challenging the notion of user power over their data (Fink, 2024).

Government interventions that claim to promote data "commons" and innovation often exacerbate labor exploitation by rendering work anonymous while providing vast datasets to businesses. This approach narrows power and proprietary rights over personal data while commodifying it to serve market imperatives in a bid to claim “national champions on the global stage” as a way to assert digital sovereignty (Athique & Kumar, 2022, Panday 2021).

For example, there is growing criticism that the Indian government aligns its data governance with market goals, reshaping public databases for both public and private sector use, prioritizing economic utility over the social value of labor. This reduces individuals to mere data owners or human capital in AI systems (Mishra, 2023; Panday & Samdub, 2024). Advocating for data rights through data as a public good, in this context ignores the complexities of labor exploitation, especially for the Global Majority (Barlett et al., 2024; Gurumurthy & Chami, 2022).

By portraying "digital subjects" as entrepreneurial agents (Irani, 2019), these narratives obscure systemic exploitation, which reduces labor to generating surplus value for AI-driven optimizations. The abstraction of labor into data commodities erases critical distinctions of class, gender, race, and geography (Mohun, 1984). The prosumer ideology deepens these inequalities by framing individuals as "data bodies" (Mager & Mayer, 2019), further entrenching divisions along lines of caste, race, and gender in the Global Majority.

18.4. Prosumer Ideology as a Condition of Data Market Expansion

Intersectional feminist critiques (Gurumurthy & Chami, 2021, Radhakrishnan 2020) highlight the importance of incorporating social power differentials into data science and ethics, advocating for embodied subjectivity and democratic participation in production. This critique challenges the disembodied abstraction of labor in platform capitalism, stressing the need for equitable representation.

As generative AI becomes integral to platform business models, debates around creative labor and intellectual property reemerge, necessitating a deeper understanding of colonial legacies and neo-colonial accumulation patterns that reinforce global inequalities. Beyond addressing data denial, it is essential to analyze the class structures that perpetuate divisions within the "digital precariat" (Standing, 2014). In the Global South, the rise of "peer-to-peer" services has further platformized domestic spaces and informal labor, deepening informality through algorithmic job allocation (Dubal 2023).

Platforms often render human mediation invisible, reducing workers to mere algorithmic components. Gray and Suri (2019) argue that the "ghost workers" behind AI should be acknowledged as crucial actors in networked publics. However, while this recognition seeks to expose invisible labor, it fails to challenge capitalist structures that systematically devalue specific forms of labor across the Global Majority.

Recognizing all labor as equal does not dismantle the structural inequalities determining labor value. A rights-based approach may affirm the dignity of work, but it overlooks the dualities of exploitation and domination (Ayalew, 2024). Such approaches risk reinforcing techno-solutionism (Duberry, 2023), particularly when governance frameworks render informal workers "computable" under the guise of digital inclusion, obscuring the underlying power dynamics.

Framing the digital precariat as a unified class of data prosumers oversimplifies diverse lived experiences, masking the unequal access to resources and opportunities within the platform economy. Defining labor through precarity falsely implies equality among those engaged in "free labor" on digital platforms, ignoring the structural differences shaping their roles.

The "sharing economy" facilitates data value exchange among "peers" through AI mediations, reducing labor to abstract data value authenticated by scientific economism (Sinha 2024). Although these metrics acknowledge diverse identities, they reinforce normative categories that exclude workers who fail to meet specific algorithmic standards. Rather than promoting egalitarian market access, this dynamic entrenches class-based marginalization. Addressing platform exploitation requires not just analyzing the power of algorithms but also recognizing the ongoing expropriation of labor through them.

Furthermore, portraying citizens as part of a "data-rich" digital precariat (Nilekani, 2018) echoes Althusser's concept of the subject as an ideological construct, which obscures the material foundations of capitalist exploitation. Focusing solely on digital sovereignty and data-prosumer rights—through frameworks like consensual data-sharing (WEF, 2022; Singh & Vipra 2019)—neglects the structural exploitation embedded in platform economies. Platforms claiming to "formalize" informal sectors (Surie & Huws, 2023) often mask class exploitation, expanding data markets while sidelining labor outside of the platforms.

Platforms like Uber and Swiggy exemplify a significant shift in the organization of labor, aggregating informal workers and commodifying every aspect of platform development. Logistics, a central component of "variegated capitalism" (Neilson & Rossiter, 2017), demonstrates how local labor regimes and consumption patterns are shaped for global exchange, reducing workers to "data bodies" and framing them as social “peers” within an abstract digital economy.

This dynamic relegates workers to fragmented roles within a rapidly expanding consumer economy, redirecting the discourse from issues of privacy and control to those of data valuation and exploitation (Singh, 2019). As a result, these systems not only deepen existing inequalities but also conceal the exploitative nature of digital labor. The ideology of prosumerism, which claims to elevate users and digital laborers as data producers (Arvidsson, 2013), simultaneously devalues the logistical labor predominantly carried out by workers in the Global South (Shanmugavelan, 2024). Framing data extraction as progressive economic development obscures the material labor that sustains it, exacerbating global inequalities (Jung, 2023).

18.5. Conclusion

Recognizing individuals as data entities has intensified claims to data rights, increasingly tying them to legal frameworks governing data exchange. This shift represents a departure from traditional notions of privacy, which emphasized withholding data from platforms, toward advocacy for individual control over data usage. However, genuine control over data necessitates collective agency in regulating digital production—a dimension that remains largely unaddressed.

Reducing users to digital prosumers or data subjects (Gandini 2021) oversimplifies deeper societal conflicts and reinforces their status as biopolitical populations (Gregory & Sadowski, 2021), treating individuals as interchangeable data points. This perspective flattens complex class relations into negotiations over data production, framing social inequality as a matter of uneven data distribution rather than engaging with the broader socio-economic divides that underpin it.

Moreover, digital users are often conceptualized as “prosumer commodities” (Flisfeder, 2016), with their autonomy shaped by platforms in data-driven markets. This dynamic reconfigures the labor-capital relationship, heightening worker precarity and complicating the classification of user activity as productive labor. The commodification of user engagement exacerbates exploitation, further blurring the line between consumer participation and labor.

As generative AI enhances content creation, disputes over data ownership are likely to intensify, exposing contradictions in commodifying user data while maintaining the illusion of personal control. It is critical to assess AI’s material impacts on labor processes rather than merely speculate on its abstract potential. While scholars such as Christian Fuchs (2013) emphasize unpaid digital labor, these frameworks risk oversimplifying class struggles, particularly in debates on AI governance.

Julie Cohen (2019) critiques how governance structures are co-opted by economic imperatives, reshaping democratic processes in favor of market interests. The "economization of governance" transforms democratic participation into a productivist role for citizens, reducing their political agency in favor of their role as economic actors—data prosumers fueling AI systems. This reduction of social interactions to data-driven abstractions turns individuals into biopolitical populations where rights and agency are claimed through data identification (Athique & Parthasarathi, 2023).

Ultimately, the rhetoric of data decolonization and digital sovereignty may, paradoxically, reinforce existing data markets by normalizing the reduction of citizens to data subjects exploited for their data potential. This normalization distracts from addressing systemic inequalities and risks entrenching structures of exploitation under the guise of empowerment.

To reclaim genuine agency, we must reject reductive distributive and productivist frameworks and advocate for an understanding of labor, one that recognizes the complex dynamics of power, inequality, and exploitation in the digital age.

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19. COST OR BENEFIT? THE IMPACT OF AI ON THE WORK OF MEDICAL PRACTITIONERS

AMRITA SENGUPTA AND SHWETA MOHANDAS

Abstract. While there is a growing interest in using AI for its speed and proposed efficiency, there are concerns over its use in the highly specialised and sensitive medical field. Through primary research with medical professionals, this essay looks at the current use of AI by medical practitioners in their research and practice, new challenges and the perceived benefits of AI for healthcare for medical professionals.This essay also briefly reviews generative AI's impact on community health workers in India. The essay suggests a more careful approach to AI adoption for healthcare so as to not cause undue burden on healthcare professionals in the short to medium term.
Keywords. Artificial Intelligence, AI in Healthcare, GenAI, AI and work

19.1. BACKGROUND

The growth of applications of AI in healthcare has proliferated globally, some of the popular use cases being radiology, telemedicine and mental health chat bots, while use of AI in drug discovery and disease surveillance have also seen an increased interest. Global studies have also suggested that AI can help in reducing treatment costs, improving health outcomes and, helping in faster diagnosis (IBM, 2024), (Alowais et al., 2023).

In the Indian context one estimate suggests that "the Indian healthcare AI market is expected to reach USD 1.6 billion by 2025"("AI In Healthcare: Changing India's Medical Landscape," n.d.). Startups like Cure.AI, Niramai and Wysa, BrainSightAI as well as big technology companies such as IBM, Microsoft and Google have already invested heavily in AI and healthcare in India (Pti, 2024). Given the rapid scale of growth and investments in AI systems, we are at a moment where adoption for AI in healthcare in India needs to be critically examined, specifically on how it impacts the work of medical practitioners and the healthcare system at large. The demand for healthcare professionals is expected to grow given the current shortage of healthcare workers in India (with a ratio of 1.7 nurses per 1,000 people and a doctor-to-patient ratio of 1:1,500 nationwide) ("Healthcare System in India, Healthcare India - IBEF," n.d.). In a currently overburdened healthcare system, the promise of AI is that of faster, efficient and cost effective diagnosis and care. However, as a build up to it, what are the demands it will put on healthcare workers in the immediate term, with additional data annotation and labelling responsibilities, learning the use of advanced and emerging technologies, and picking up additional data management responsibilities, among others? In India, especially since the process of digitising healthcare is still nascent, there is a need to look at if and whether AI is actually living up to its promises and acting as an aid to medical professionals if not a replacement.

In addition, with the growth and large-scale adoption of Generative AI (GenAI), there has been an increased pattern of information seeking on platforms such as ChatGPT. While there are certain benefits to be derived from such use, it also raises questions on how physician's over-reliance on (GenAI) responses in clinical decision making could impact patients, medical practitioners as well as the healthcare system at large, some deliberations we hope to get into through the course of this essay.

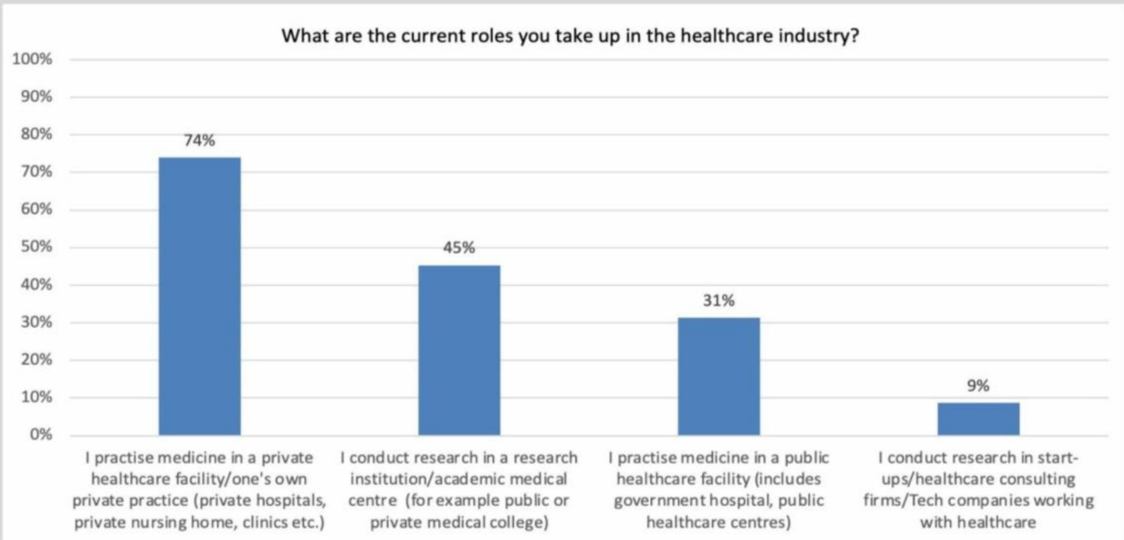
In this essay, we present findings from our research on how medical professionals currently use AI for healthcare, the perceived benefits and pitfalls of using AI, specifically how it impacts the work of medical professionals, and a few provocations for future implementation of AI systems in India in the wake of (GenAI).

19.2. METHODOLOGY

As part of a larger mixed methods, Institutional Review Board approved study on Al and healthcare in India, we conducted three surveys with 500 respondents across three prominent stakeholder groups - medical practitioners and researchers (150 respondents), respondents from healthcare institutions (150 respondents), and respondents from technology companies and startups developing and deploying healthcare-focused Al models in India (200 respondents). We also did 18 qualitative interviews with medical professionals, startups, technology companies, civil society members, and policy makers.

In this essay, we focus specifically on the medical practitioner and researchers' survey with 150 respondents and the interviews with five doctors, and ten technology companies and startups from the larger study. Data collection for the surveys and interviews were conducted between January and April 2024. The below chart lays out the split of the medical professionals surveyed by their roles.

Figure 2. Responses from medical professionals on their use or research in Al in particular areas.

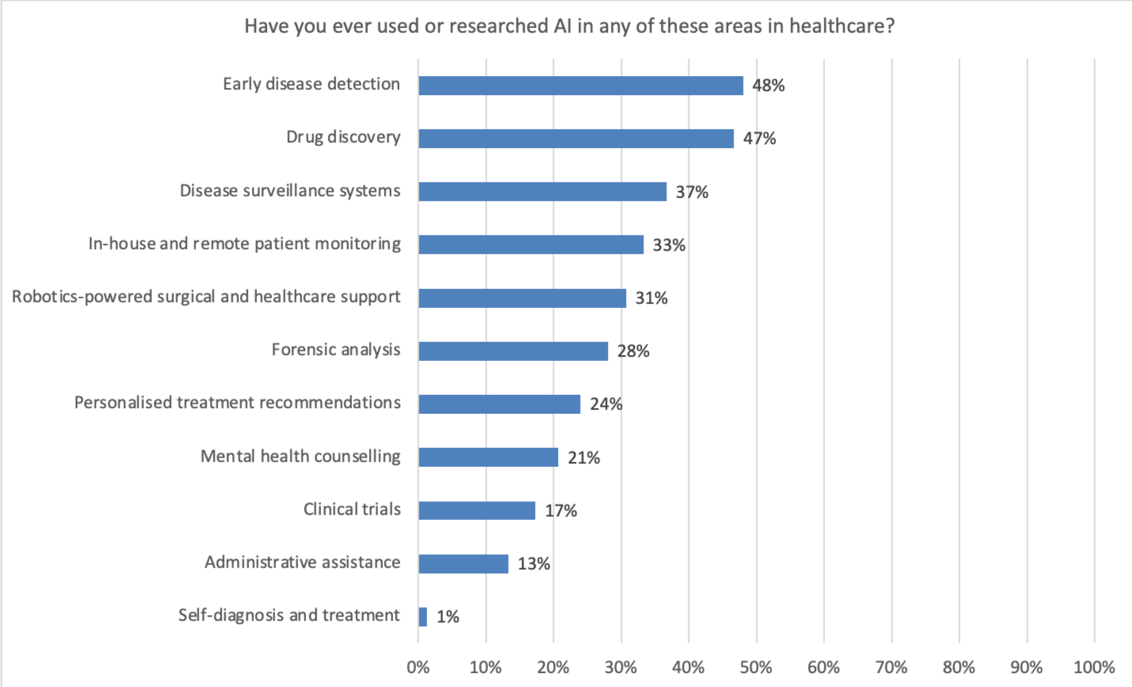


Source: CIS Survey of medical practitioners in AI and healthcare, January- April 2024, n = 150.

19.3. CURRENT USE OF AI BY MEDICAL PRACTITIONERS IN THEIR RESEARCH AND PRACTICE - INSIGHTS FROM OUR STUDY

As seen in Figure 1, our survey revealed that a lot of AI related work was limited to research in particular areas as opposed to actual implementation. Early disease detection and drug discovery were the most picked areas of use and research in healthcare. Administrative assistance was one of the lowest-picked choices, which potentially points to the lack of access to standardised processes and digitised data that could be used for training AI for administrative assistance.

Figure 3. Responses from medical professionals on their use or research in AI in particular areas. This was a multi-select question



Source: CIS Survey of medical practitioners in AI and healthcare, January- April 2024, n = 150.

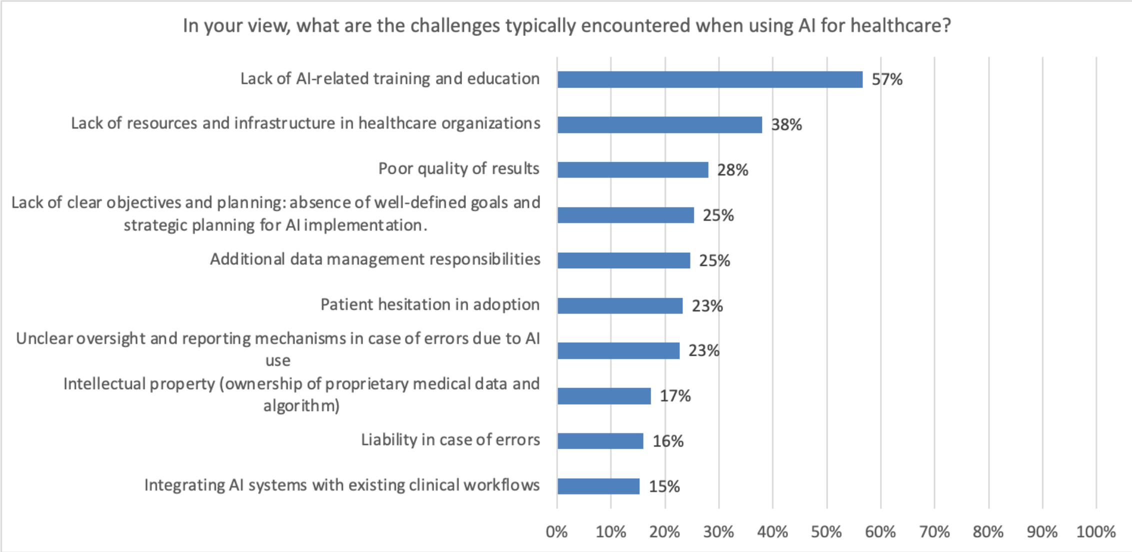
Through our interviews and interviewee profiles we gathered that the most common use cases of AI in India include diagnosis such as cancer screening, chatbots for mental health, drug discovery, and remote monitoring, and for administrative assistant and patient management functions. However all the doctors we interviewed stated that the use of AI in their workflow was not yet widespread. The use of AI was also limited to mostly private hospitals. In our interview with one doctor working in a large public hospital they stated that AI was being currently implemented in research stages and the AI use was currently limited to administrative tasks.

19.3.1. *NEW CHALLENGES BROUGHT BY AI FOR MEDICAL PROFESSIONALS*

In our survey, medical practitioners expressed several concerns that they experienced while using AI for healthcare. Nearly 60% medical practitioners expressed the lack of AI-related training and education as a big barrier to adoption of AI systems. While 25% respondents also reported additional data management responsibilities as a challenge, which points to the burden that AI use is creating for medical practitioners.

Nearly one in four medical practitioners in our survey mentioned additional data management responsibilities as a challenge when it came to integrating AI into their work. Doctors have also raised concerns of the efforts and infrastructure required on their side to digitise health records, such as administrative assistance (“Ayushman Bharat Digital Mission: Boon or Bane?,” 2023) and the cost of data security(Karpagam, 2021).This was pointed out in our survey as well, with 38% medical practitioners citing the lack of resources and infrastructure as a challenge while using AI for healthcare (see Figure 3).

Figure 4. Responses from medical practitioners on the question of challenges faced while using AI for healthcare. This was a multi-select question



Source: CIS Survey of medical practitioners in AI and healthcare, January- April 2024, n = 150.

While there have been reports of state governments encouraging the use of AI in healthcare with initiatives such as the screening for kidney disease ("State Government to Screen Kidney Diseases With AI-powered Mobile App," n.d.) and tuberculosis(Yasmeen, 2024); the use of AI is mostly limited to private hospitals ("Progress of Healthcare Artificial Intelligence in India," n.d.).Hence the benefits of AI like reduced costs, efficiency, and reduced burden on doctors is yet to reach the areas where it is needed the most—-the public healthcare system.

Through the AI life cycle for healthcare, medical practitioners would be required to intervene at various stages of AI implementation from data collection to train the AI systems to deployment and use of AI systems by the medical practitioners.The following paragraphs shed light on how medical practitioners engage in these stages, with insights from our in-depth interviews.

In data collection; the lack of India specific data requires medical professionals to digitise and annotate the data in addition to their clinical and administrative work. The issue of data security especially is also more emphasised after multiple health data leaks (Singh, 2024). It was highlighted by interviewees from civil society that the medical professionals in addition to data collection had to spend out of pocket to ensure security of this data.

In development; where the AI system is made and trained by technologists, and medical practitioners are seldom involved in its creation. It was pointed out by civil society interviewees that often medical professionals are not actively involved in the development of the AI systems, thereby making them mere end users. In our interviews with doctors, however, they stated that they worked with startups in developing, and providing feedback to AI systems (Pti, 2023).

In deployment; the still high cost of AI and existing infrastructural challenges with healthcare in India, means that the doctors and hospitals are still not able to adopt AI systems as easily (Alkhaldi, 2024). It was highlighted by an interviewee from a tech company that hospitals are still grappling with the idea of accommodating AI systems in their existing workflows and still deciphering how to book AI to their expenses (whether as devices or an IT expense). They also stated that the high cost of AI had to be justified in order for hospitals to purchase them, and then proceed to make up the costs from the patients.

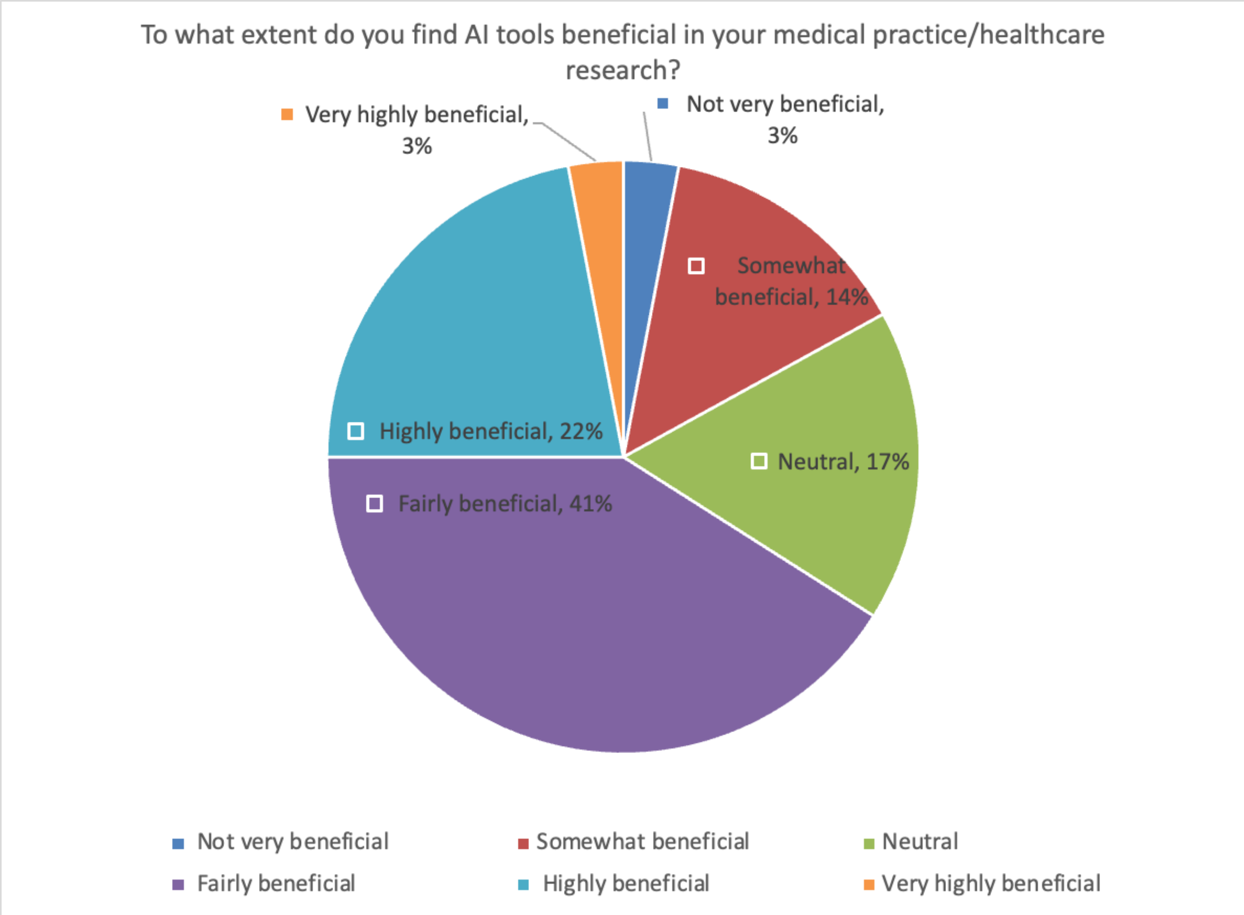
In terms of AI workflows, post deployment as well, these systems are currently being used as a tool that compliments the doctor's decisions. However this in turn adds another layer of work for the medical professional who cannot blindly follow the AI system's results.

19.3.2. PERCEIVED BENEFITS OF AI IN HEALTHCARE

There are some benefits that AI in healthcare can bring. As secondary literature suggests, one such example is its use in disease surveillance, which due to the large amount of data and compute power that AI uses, offers a significant advantage. AI is being used to predict future outbreaks as well as help public health officials be better prepared and proactive (Anjaria et al., 2023). An example of this initiative in India is the Dengue Dashboard established at IISC (Artpark, n.d.). Similarly in drug discovery, AI's potential to transform every stage of the workflow is being explored. Currently AI is involved in drug design, decision making; determining the right therapy for a patient, and managing the clinical data generated(Chun, 2023). In India AI was used to examine potential drugs for Covid -19 treatment (ET HealthWorld, 2020). The use of language data and text to speech has also been helpful in providing multilingual support through chat bots such as Wysa ("FAQ - AI Chatbot | Online Therapy," n.d.), which provides mental health support in Hindi and a few other languages, and HealthifyMe provides multilingual support to maintain nutritional goals (Saha, 2024).

In our survey, medical practitioners also shared their views on whether they find AI beneficial and in which areas (see Figure 4 and Figure 5).

Figure 5. Responses on how medical professionals view AI as a tool in their medical practice/healthcare research (question was asked on a likert scale of 1 to 7, single-select)

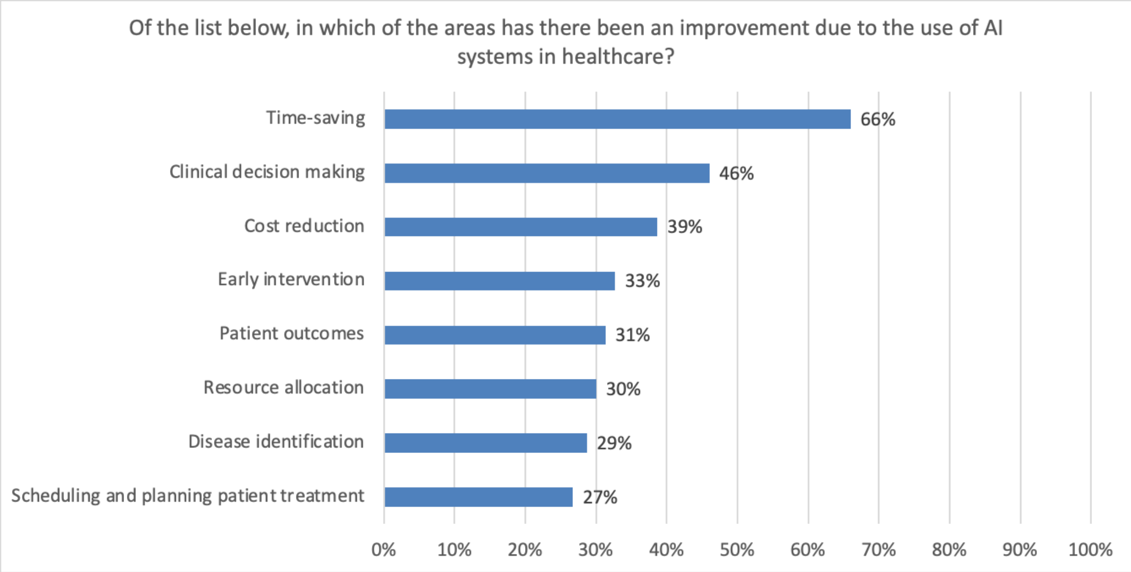


Source: CIS Survey of medical practitioners in AI and healthcare, January- April 2024, n = 150.

In our survey, 41% of medical professionals suggested that AI could be fairly beneficial in healthcare or healthcare research (see Figure 4). Further, when it came to realising the benefits of AI, medical professionals saw time saving as the most noted benefit, followed by improvement in clinical decision making (see Figure 5).

This could have certain potential risks that have been highlighted in various research studies from the last many years, including but not limited to questions of liability in case of AI based decision making, over-reliance on AI leading to loss of/negative impacts on clinical skills, representational biases that the AI models may present (Ameen, Wong, Yee, & Turner, 2022), especially so if the source of data is not the same as where the AI system is being administered.

Figure 6. Responses from medical professionals on areas where they have seen improvement due to AI. This was a multi-select question



Source: CIS Survey of medical practitioners in AI and healthcare, January- April 2024, n = 150.

19.3.3. Generative AI and its impact on community health workers in India

While our survey and interviews didn't directly or extensively investigate the use of Gen AI for healthcare, given its rapid adoption, it would be remiss to not reflect on its impact on healthcare in India. In this section, through existing secondary literature and our analysis, we look at ways in which it can have positive and some negative impacts when used for healthcare in the Indian context, especially in public health.

Accredited Social Health Activist (ASHA) workers who are community health workers are the first point of care between the family and public health system, through collecting data, providing basic curative care, and promoting universal immunisation("About Accredited Social Health Activist (ASHA)," n.d.). Due to their reach they could be provided with smartphones compatible with dedicated AI screening applications, something which has seen some success in infant care (Ai, 2023) and GenAI could be explored to help them make quick initial diagnosis and screening about a person's health, and prioritise care. Gen AI could also be used for translations to reduce the language barrier.

As stated earlier AI has seen success in disease surveillance and prediction. With the amount of data, speed and the right training of community health workers and public health professionals in Gen AI applications, it could be used to collate large amounts of data from multiple sources such as data provided by community health workers, hospitals, and social media and provide faster analysis of the spread of a disease, making policy decisions and implementation easier (Bharel, Auerbach, Nguyen, & DeSalvo, 2024).

While Gen AI has potential to improve healthcare delivery in India, there are also some perceived concerns it could bring especially with respect to medical professionals. One of the issues that could arise is over reliance on these systems in their work which could make them less attuned to their innate skills and observations. The easy access to GenAI systems could also mean that patients could also self-diagnose and self-medicate which could lead to medical emergencies (MacMillan, 2024). The absence of a liability framework and guidelines on the use of GenAI in practice could also mean that the medical professionals use this at their own risk and without proper training and support from institutions.

CONCLUSION

While AI is not set to replace medical professionals, there is still an uncertainty of what roles it will play in healthcare. As also seen in the survey and interview data the nascent stages of AI in healthcare in India mean that medical professionals are still using AI more as an added step to their existing workflow and spending time improving the AI system through their feedback. On the other hand AI has also seen success in the larger context in areas with large manpower and expertise such as disease surveillance, and drug discovery, which have an immense potential to help in public health as well as reduce time it takes to make decisions and analyse trends. It is here that GenAI could improve their capacities and help regions like India where timely interventions could benefit both the public health system and the public. Hence while AI and in the future GenAI has the capacity to help healthcare, we need to prioritise areas where there could be most benefit and is in larger public interest with the least disruption to the existing workflow and be considerate of whether the costs (manpower as well as work time) outweigh the benefits.

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20. REIMAGINING EDUCATION: POTENTIAL SOLUTIONS FOR NOMADS

FAIZO ELMI

Abstract. This essay examines the transformative potential of artificial intelligence (AI) in enhancing educational opportunities for nomadic populations. By leveraging AI technologies, such as adaptive learning platforms and virtual classrooms, educational access can be tailored to meet the unique needs of mobile communities. The essay explores how AI-driven tools can provide personalized learning experiences, bridge educational gaps, and support continuous learning despite geographical constraints. It also addresses the challenges of integrating AI in such contexts, including technological infrastructure and cultural considerations. Ultimately, the paper argues that AI holds significant promise for delivering equitable and flexible education to nomadic groups.

INTRODUCTION

A common assumption with the term “nomadic” is that it is a culture that is fundamentally at odds with the modern world. For centuries, nomadic populations have resisted industrialization, modernization, and domination. In fact, nomadic populations are largely considered to be "aimless wanderers, immoral, promiscuous and disease-ridden" peoples (Hill & Randall, 2022). While this mindset is untrue and condescending, the fact remains that nomadic people live in such a way that makes traditional access and implementation of education rather difficult.

The idea of traditional education is often met with distrust among nomadic groups. Historically, the issue of educating nomadic populations has come from one of two viewpoints (Dyer, 2006). First, many academics suggest that education would allow for nomadic populations to assimilate into settled society. The second more altruistic reason relates back to the United Nations Children Fund (UNICEF) stating that education is a human right and a key factor in reducing child labour and poverty (Dyer, 2006). Rapidly developing technology can now allow for nomadic education to no longer be approached from an either-or mindset. With some flexibility and modern technology, there are possibilities to meet in the middle. With a majority of nomads living across Africa, this issue is especially poignant.

20.1. TRADITIONAL NOMADIC APPROACH TO EDUCATION

Traditionally nomadic people have provided their children with a fulfilling education, with little to no say from institutionalized powers (Krätli, 2001). The environmental, economic, and historical knowledge that children needed to know was passed down from generation to generation. This equipped nomadic children with the appropriate skills and context to not only survive in their respective domains, but also attain professional positions within their respective societies (Krätli, 2001). The nomads became proficient in whatever local knowledge that was needed.

Beginning with the decade following the Second World War, rapid industrialization merged with post-colonial borders began to create a society that deemed nomads as being obsolete (Dyer, 2006). Modernization has made it challenging for nomadic people to continue with their traditions and many of their education systems are no longer adequate in preparing their children for their adult lives (Dyer, 2006).

Formal education was largely considered to be a waste of time by many nomadic groups (Jama,1993). School curriculums have been criticized by nomadic educators for being “made by sedentary people for sedentary people” (Dyer, 2006). For many nomads, the content that was being presented in these curricula, were not at all practical to their lived realities. Lack of applicability would eventually translate into lack of interest, and result in nomadic groups across the globe having some of the highest dropout rates in their respective countries (Dyer, 2006). Additionally, nomadic children are more likely to experience cultural alienation when they do attend school. Nomads often have a strong sense of pride in their identity, as nomad Krätli writes:

> *“Pastoralists' strong sense of dignity is linked to pride in their own identity as pastoralists, nomads and a distinct ethnic group. Such a perception of themselves may be increasingly undermined by propaganda depicting them as ignorant, poor, dependent and powerless, made even more destructive by a feeling of being cheated in almost all interactions with the wider society” (Krätli, 2001).*

Seeing as how one of the more common solutions in educating nomadic children is boarding school, it is not shocking to think that students would begin to identify more with the dominant culture.

20.2. CHALLENGES WITH EDUCATING NOMADIC POPULATIONS

There are many technical and cultural challenges involved in educating nomadic populations. As mentioned earlier, lack of applicability is one of the more common reasons, but there are also several other factors that contribute to the issue as well.

More often than not, nomadic groups are situated in remote areas that would require a great amount of effort to reach. This makes it difficult to provide both teachers and resources in those sparsely populated areas. In addition to this, migration patterns also determine when nomads will be in a certain area and for how long (Jama,1993). With many settled schools being either unable or unwilling to work to accommodate nomadic children results in high truancy rates among nomadic children (Dyer, 2006). Furthermore, seeing how nomadic groups also consistently have issues relating to poverty often mean that even those willing cannot afford to send their children to boarding schools, or pay for their upkeep in a settled village (Jama,1993). In addition to this, traditional education often undermines indigenous structures of education (Jama,1993).

Arguably most importantly is what refers to as the opportunity cost associated with sending children to schools. Children in many nomadic groups have certain responsibilities they are expected to tend to. These often involve aspects of animal husbandry, family rearing, or other domestic tasks (Krätli, 2001). For many families this loss of a child would cause a significant burden in the household. What’s more is the physical aspect of moving to and changing a family’s entire course to be in closer proximity to a school is usually a hefty task. Particularly for pastoral nomadic families, who rely heavily on seasonal migratory patterns of animals (Jama,1993).

20.3. PREVIOUS ATTEMPTS AT EDUCATING NOMADIC GROUPS

One of the more common solutions that have been utilized in the past is the creation of boarding schools. The goal was to provide suitable living conditions for nomadic children in hopes that this would improve student retention. However, boarding schools have also been unable to attract a large nomadic population. This is due to several reasons, one of which being the division within the family structure (Carr-Hill, Sedel , Eshete, & de Sousa, 2005). Children were being socialized away from their communities, resulting in a feeling of isolation from their communities. Krätli writes "when it comes to boarding school, no nomadic parents or children wish to be separated for long periods, usually with no way of communication. He also argued that the parents do not like the idea of giving custody of their children to people they do not know, to whom they are not related and whose moral integrity they often doubt" (Krätli, 2001).

20.4. Case Study: Somalia

Somalia is largely arid and desert in climate, and a vast majority of the population were either nomadic or semi nomadic in nature (Konczacki, 1967). A devastating drought during the early 1970's caused immense damage to the Somali nomads traditional way of life in a way that it was never truly able to recover from (Shirwa, 1999). Currently, 32% of the population are still nomads (Federal Government of Somalia, 2022). These groups often move around in search of water and grazing areas for their livestock (Lewis, 2024). The semi-nomadic population remain in parts of the south living a more agro-pastoral life, but still rely heavily on their livestock for their survival (Lewis, 2024).

While education in Somalia is a right and largely considered by the population to be a means for good, mistrust between nomadic groups and the government have resulted in very little improvement regarding the education of nomadic children. Several of the issues previously highlighted regarding reluctance in enrolling children in schools appear in conversation with Somalia nomadic parents. Household labour, lack of applicability and alienation are some of the reasons Somali parents are unwilling or unable to educate their children (Carr-Hill, 2015). The three most common reasons in this case were due to lack of availability, income, and constant migration (Carr-Hill, 2015). This paints the image that while enthusiastic about the prospect of education, it is not convenient enough for many pastoral nomads.

Technological development and education have arguably been interconnected since the printing press allowed for knowledge and information to be far more easily available. In 2022 when ChatGPT catapulted AI into the public consciousness, it sparked debates surrounding the role of AI in the classroom. To what extent could it be adapted to benefit both students and teachers? UNESCO's Global Education Monitoring Report 2023 states "these new tools can prove invaluable in providing personalized support for students, particularly those with disabilities or living in remote areas" (2023). In regards to nomadic children, AI can be particularly useful due to its personalized and flexible access. Despite their mobility and accessibility issues, nomadic children can still receive an education.

Ultimately, the goal of utilizing AI in this specific case would be to provide an education for nomadic children that caters to unique traditions and way of life. Using the Somali example, as of 2024 roughly 85% of Somali adults own a mobile phone (75, 2024). Seeing as though a majority of financial transactions in Somalia are done via the internet, it can be assumed that this is a largely technologically-literate population (75, 2024).

The solution being proposed is to take advantage of this perfect storm of able participants. Beginning with the creation of a primary education server that can be accessed offline. Ideally, students in their primary years would be able to access a wide variety of learning resources that they would learn from while working alongside an AI tutor. Charity Help International (CHI) utilizes technology from two non profit organizations to create exactly this.

Learning Equality was founded in 2012 as a hopeful solution to the inequality present in internet access across the globe (2024). It would eventually go on to become a non-profit organization specializing in aiding educational equity through technology. With the ultimate goal behind the project being inclusivity, Learning equality emphasizes the importance of creating inclusive educational experiences for the widest range of students possible (2024). Aside from providing access to offline learning opportunities, it also utilizes Kolibiri, an open source education platform that provides educational services without the need for internet access (2024). Most importantly, educators can individually manage their own content, making this easy to tailor to local needs and curriculum (2024). The second organization is Kiwix. Which is essentially a free offline library that condenses various websites and articles in such a way that they are able to be easily downloaded and stored (2024). Together, both of these programs create an educational server that can be accessed through any piece of technology that is either Windows or Linux based. CHI in particular emphasizes that second hand technology (to a degree) is most cost efficient.

Learning Equality, and other programs of the sort have the potential to provide nomadic communities with both technological resources and access to quality education. Additionally, through the use of AI programs can be taught to create tailor made lessons for individual students that are both culturally sensitive and relevant. Not only would this contribute in bridging the educational gap, but it would also aid in improving digital literacy skills among students, and empower local communities by showing respect for their choices and traditions.

While this solution does have many benefits, it should be noted that there are certain challenges that would come along with implementing programs such as these on a wide scale. For instance there would be significant limitations on the technology itself. Whether that be due to charging issues, storage concerns, or simple repairs, there are certain logistical issues that need to be met in order to guarantee success. Moreover, there is the nomadic community itself to consider. If they themselves are not involved during both the planning and implementation of this project, there may be some cultural disconnect that could cause unnecessary barriers.

In the case of Somali nomads, if a program such as the one mentioned above was institutionalized on a large scale, it has the potential to solve several problems surrounding educating Somalia's nomadic community. It would no longer be required for students to physically attend schools. This would mean that nomads would not have to arrange their travel plans around the accessibility of a school. Additionally, students would not have to be separated from their families for prolonged periods of time. Instead they would be able to work from the comfort of their own home. No longer would parents have to choose between alienating their child from their families or providing them with a decent education. This close proximity to home would also mean that the traditional practices of the nomads would be maintained. The funds that would have also been spent on school related necessities (uniforms, books, boarding) could also be reallocated back into the home. Without the confines of a traditional classroom, students would also be able to work at their own pace. This would make them available to participate in household labour when it was needed of them (to an acceptable degree).

Remote schooling would also allow for a certain amount of flexibility in learning. Students would be able to move through material at their own pace, this would be particularly beneficial for students who may have irregular schedules due to their travels. It would also mean continuity for these students as well. Without having to start afresh with their education every time they find themselves moving, students can move through their schooling without interruption. Even students who may have certain learning disabilities can benefit from this, as Learning Equality offers a wide range of resources in their lessons. These include interactive videos, texts, audio lectures, and more that can all help students of different abilities.

The Basic Accelerated Education Program in Somalia is a program that seeks to improve access to a quality accelerated education for out of school youth (Federal Government of Somalia, 2022). In 2022 alone, improving access alone cost roughly 762,720$ (Federal Government of Somalia). If a program such as this was to be either partially or completely replaced by an AI remote learning platform of sorts, the costs associated with creating and new infrastructure could be reverted into investing towards remote learning programs. This would financially make accessing education easier for nomadic groups who historically spend the least on schooling, while also improving on the flexibility aspect of the program that the Ministry of Education prides itself on (Federal Government of Somalia, 2022).

In conclusion, AI offers a transformative opportunity to address educational disparities faced by nomadic populations. By integrating adaptive learning technologies and virtual classrooms, AI can tailor educational experiences to the unique needs of mobile communities, facilitating continuous and personalized learning regardless of location. However, successful implementation requires overcoming challenges related to technology access and cultural adaptation. Embracing AI in education for nomadic groups can bridge gaps and create more equitable learning opportunities, but it must be approached thoughtfully, with consideration of both technological and socio-cultural factors. As AI continues to evolve, it holds the potential to significantly enhance educational outcomes for nomadic populations.

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21. The Need for Transnational Perspectives on the Social, Legal and Environmental Impact of Artificial Intelligence

Jess Reia, Rachel Leach and Anuti Shah

Abstract. The popularization of artificial intelligence (AI) models imposes various challenges, from human rights violations to energy consumption. While sustainability has been part of the AI agenda for years, environmental justice (EJ) is still making its way into AI regulatory frameworks. This essay discusses the need for transnational, climate-centered perspectives on AI regulation. Three questions guide this work: (1) Are EJ concerns considered when regulating and governing AI? (2) How do geopolitical power dynamics play into the environmental impact of AI? (3) How can EJ in AI regulation be improved? Here, we propose an exploratory analysis of cases in the US and Brazil.
Keywords: artificial intelligence; AI regulation; environmental justice; AI governance; climate crisis.

Introduction

Artificial intelligence (AI) models' increasing presence in the public debate, decision-making systems, and everyday life requires quick regulatory and policy answers. With a technological transformation spearheaded mostly by the private sector and its ability to shape research (Burrell & Metcalf, 2024), concerns around the technologies social, legal and environmental impact are receiving growing attention. The popularization of large language models (LLMs) and generative AI (genAI) have brought challenges from human rights violations to massive amounts of energy and water consumption.

While sustainability has been part of the AI agenda for years across countries (Wang et al., 2024), including the promise of AI as a solution to the climate crisis and tool to achieve the Sustainable Development Goals (SDGs) (Vinuesa et al., 2020), environmental justice is still making its way into AI regulatory frameworks and policies. As environmental concerns are becoming more visible, issues of justice and sovereignty must not be overlooked. The official narrative at meetings 28 and 29 of the Conference of the Parties (COP), the United Nations (UN) Climate Change Conference, promotes "leveraging AI" for all to create opportunities for the energy and technology sector to work together (COP28 UAE, 2023). However, this narrative dismisses perspectives of other sectors and community organizations engaged in exposing the harms caused by AI systems.

The idea that AI systems exist in the cloud, disconnected from everyday life and material resources has been widely questioned by parts of academia, civil society, and grassroots movements (Bender et al, 2021; Castro et al., 2024; AlgorithmWatch, 2022). Beyond perpetuating colonial and digital extractivist practices (Ricaurte, 2019; Iyer, 2022), the expansion of big data infrastructure also poses threats to digital sovereignty (Belli & Hadzic, 2023) in global majority countries. Territories where valuable, scarce resources are available for extraction, like the lithium triangle (Chile, Bolivia and Argentina), are uniquely at risk. As Brazil regulates AI and prepares to host COP30 in 2025, concerns about digital infrastructure, sovereignty and human rights come to the forefront.

This essay's goal is to discuss the need for transnational perspectives on AI regulation that consider social and environmental justice components. The questions guiding this work are:

1. Are environmental justice concerns part of the process of regulating and governing AI internationally?
2. How do geopolitical and industry power dynamics play into the environmental impact of AI transnationally?
3. What are the first steps to improve environmental justice in AI regulatory frameworks?

To respond to these questions, this essay proposes an exploratory analysis of AI regulatory frameworks in the U.S. and Brazil. The impact of U.S. based Big Tech companies extends beyond borders, impacting the geopolitics, sovereignty and the environment in the global majority, highlighting the need for comparative and transnational studies. The findings presented here are part of a larger project funded by UVA's Environmental Institute addressing the impact of incorporating AI systems in electric vehicles. The methods used were literature review, legal and policy analysis, and compilation of publicly available secondary data.

The first section investigates environmental and sovereignty imbalances caused by massive AI deployment. The second section briefly analyzes the concerns related to environmental justice in current AI regulatory efforts in two countries, United States and Brazil. Lastly, a brief exploratory attempt at considering environmental justice when regulating and governing AI that considers the global majority is presented.

21.1. The Geopolitics of AI: Sovereignty and the Environment

AI models, even the ones designed to mitigate the climate crisis, have a significant carbon footprint. They require an extensive chain of development which includes extraction of natural resources, manufacturing of materials and equipment, model training and deployment, and disposal. Despite this environmental cost, and emerging criticisms of Big Tech companies, leading AI developers continue to have revenues higher than the GDP of some countries (Patterson et al., 2021; Luccioni et al., 2022; Erdenesanaa, 2023; Vries, 2023; Microsoft, 2023).

The concept of embodied carbon, which accounts for "emissions associated with upstream—extraction, production, transport, and manufacturing—stages of a product's life," is useful to understand the full carbon footprint of AI (U.S. Environmental Protection Agency, 2024). Unlike other industries such as construction, standards governing AI do not "provide the methods to measure the embodied carbon within technology systems from a holistic systems-thinking perspective", ultimately leading to many upstream harms being overlooked and underregulated (Mulligan & Elaluf-Calderwood, 2022). Consequently, the proliferation of AI has impacted several "water-stressed regions, draining lakes and rivers while accelerating the displacement of vulnerable populations" (Hogan & Richer, 2024). For instance, data centers are often located in Latin America due to "lower environmental regulations than the U.S. and Europe" and cheaper access to resources despite the high risk of intensifying climate change-induced drought" in the area (McGovern & Branford, 2024). AI also often uses rare minerals extracted from "zones with lax labour regulations, using methods that ravage landscapes, contaminate groundwater, and destroy natural habitats" (Hogan & Richer, 2024).

Along with upstream effects, the rapid and increasing energy use of AI model training and deployment creates additional environmental disparities. Specifically, "since 2012, the amount of computing power required to train cutting-edge AI models has doubled every 3.4 months" (Kanungo, 2023). As such, currently "training some popular AI models can produce about 626,000 pounds of carbon dioxide, the rough equivalent of 300 cross-country flights in the U.S." while "a single data center can require enough electricity to power 50,000 homes" (Rakhmanov, 2024). This rapid and expanding energy use affects "the world's most marginalized communities first" (Bender et al, 2021) as climate change destroys infrastructure (U.S. Global Leadership Coalition, 2021).

These environmental disparities are deeply connected to geopolitical and sovereignty issues. "Energy sovereignty" advocates and scholars work to shift understandings of who has a right to make decisions about energy from the current empowerment of large, almost entirely U.S.-based companies, which often work against the "self-determination and non-domination" of countries whose resources and energy they are extracting, and towards understanding energy "as a natural commons" respecting "the right of particular communities to decide on energy matters without the demand to increase profits" (Timmermann and Noboa, 2022; Stash Team, 2024; Del Bene, Soler, & Roa, 2019; Castro et al., 2024). Access to energy is a crucial issue of justice across many countries – in Brazil, a study led by Instituto Pólis found that "36 per cent of families spend at least half of their monthly income with power used for cooking and electricity, compromising" leading food insecurity and other economic issues (Instituto Pólis, 2024). So, as AI models consume extensive amounts of energy, countries must be able to understand and regulate these systems and their externalities (Belli et al., 2024).

21.2. Environmental Justice in AI Regulation and Policymaking

Environmental concerns are generally part of the AI agenda globally, but environmental justice concerns do not appear clearly in current regulatory efforts. Below we investigate how policymakers in the U.S. and Brazil are considering environmental issues in AI regulatory discussions.

21.2.1. United States

In 2023, the Executive Order (EO) on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence set the federal agenda for AI regulation in the U.S. This Order explicitly operates under the assumption that AI is a tool with potential to "enable the provision of clean" electric power, without examining the environmental issues raised by the technology itself (Exec. Order No. 14110, 2023). In doing so, this EO, along with subsequent Executive actions, reinforces the idea that AI systems are a solution to, rather than a component of, unsustainable energy use and environmental harms. Ultimately, these assumptions contribute to the sidelining of environmental justice in AI regulation, policymaking, and funding in the United States.

Federal guidance on AI funding and investment encourages the rapid development of AI systems without due consideration of environmental justice. For instance, The National AI R&D Strategic Plan, which outlines priorities for Federal AI investment, suggests only technical solutions to the environmental harms of AI, such as designing "resource-aware AI algorithms" without mentioning the disproportionate impact of these harms (U.S. Select Committee on Artificial Intelligence, 2023). Other relevant Executive guidance, such as the National Institute of Standards and Technology (NIST) AI Risk Management Framework on Generative AI and the Office of Management and Budget (OBM) Policy on Government Use of AI encourage the application of AI systems to "address the climate crisis" without due consideration of their disproportionate environmental impact (The National Institute of Standards and Technology, 2024; U.S. Office of Management and Budget, 2024). Even the voluntary agreement from Big Tech companies to "Manage the Risks Posed by AI" only mentions AI as a possible solution to climate problems, not as a contributor to them (The White House, 2023).

One of the only places environmental justice concerns are discussed is by the National Artificial Intelligence Advisory Committee (NAIAC), a committee under the Department of Commerce to advise the President on AI. In early 2023, before the Executive action discussed above, they cite research on the considerable energy use, water use, and extraction underpinning current AI systems; yet these considerations are not extended to more impactful documents within this group, nor to other regulatory and legislative efforts regarding AI (National AI Advisory Committee, 2023; National AI Advisory Committee, 2024).

Along with Executive action, the U.S. Senate created a Bipartisan AI Working Group to gather information on AI conducting forums largely made up of industry representatives. Their recommendations do not mention environment, climate, or sustainability, and addressing the "rising energy demand" of AI is mentioned only to "ensure the U.S. can remain competitive with the CCP and keep energy costs down" (The Bipartisan Senate AI Working Group, 2024). Earlier in 2024, Senator Markey introduced the US AI Environmental Impacts Act, "the first legislation to explicitly refer to the environmental impacts of AI" (Adams, 2024). However, no action has been taken on this bill since it was referred to the committee in February.

21.2.2. Brazil

The South American country has a prominent role in international multistakeholder spaces of internet governance and data protection, previously paving the way for AI regulation with the Brazilian Civil Rights Framework for the Internet (2014) and the General Personal Data Protection Law (2020). Attempts to regulate AI in Brazil started with the launch of the Brazilian Strategy for Artificial Intelligence (EBIA) (Brazilian Ministry of Science, Technology, and Innovations, 2021; Belli et al., 2023), even though legislators tried to propose draft bills ("*projetos de lei* – PL") between 2019 and 2021 (PL 5051/2019, 5691/2019, 21/2020, 872/2021), unsuccessfully. Regardless of the efforts to improve civic engagement with these bills and the EBIA, "[...] researchers and civil society advocates have been pointing out the lack of consideration given by public authorities to the suggestions of participants in consultative processes" (Belli et al., 2023, p. 2).

In 2022, the Brazilian Senate appointed a Commission of 18 Legal Practitioners to help draft the AI regulatory framework for Brazil. Quickly, civil society organizations and scholars criticized the lack of diversity, pointing out that all members were white and did not represent the majority of the population, who would most likely be affected by bias, algorithmic discrimination (Kremer et al., 2023) and climate change. Experts called for interdisciplinary contributions and broader social participation (Rená, 2022). In response, the Commission scheduled twelve public hearings and launched a public consultation process, resulting in the current draft bill, PL 2338/2023, which is under discussion.

PL 2338/2023 covers various issues, mentioning the protection of the environment and sustainable development as principle, and states that AI agents must report to the competent authority the occurrence of serious security incidents, including severe damage to the environment. In an open letter released by a coalition of civil society organizations working toward digital rights and public interest technology suggested a list of possible improvements to PL 2338/2023 including "minimum rules to safeguard the rights of affected individuals, obligations for AI agents, governance measures, and the definition of a regulatory framework for oversight and transparency" (Bernar, 2024). There is a brief mention of the role of AI in exacerbating climate change, but no further recommendations.

Despite Brazil's strong environmental frameworks, including the National Policy on Climate Change (12187/2009), AI regulation has paid little attention to the environmental impact of models like LLMs and genAI. On July 30, 2024, following the G20 summit, the Brazilian government launched the Brazilian Plan for Artificial Intelligence, with BRL 4 billion in investments to address extreme weather, develop renewable energy, and build a supercomputer. While there are hopes that PL 2338/2023 will incorporate climate action, industry associations oppose stricter regulations, arguing it would hinder innovation and make Brazil less attractive for data centers (Viana, 2024). With its vast water resources and the Amazon, addressing climate action in AI regulation is urgent.

Table 2. Preliminary summary of the status of AI and environmental impact regulation in the U.S. and Brazil

COUNTRY	STATUS OF AI REGULATION	GUIDELINES & PRINCIPLES	IS THE ENVIRONMENTAL IMPACT OF AI ADDRESSED?	RELEVANT ENVIRONMENTAL REGULATION	RELEVANT STANDARDS	OVERSIGHT AGENCIES, BOARDS & REGULATORS
UNITED STATES	No comprehensive federal legislation or regulations	White House Executive Order 14110; White House Blueprint for an AI Bill of Rights, with contributions from panels including "industry stakeholders to technology developers to other experts across fields and sectors" and received 130 responses to the RFI	Partially, as seen in government, industry, and academic groups, AI is largely understood as a beneficial tool for climate and sustainability issues, rather than a contributor to them	National Environmental Policy Act (42 USC 4321); Clean Air Act (42 USC 7401); Clean Water Act (33 USC 1251); Endangered Species Act (16 USC 1531); Resource Conservation and Recovery Act (42 USC 6901); Comprehensive Environmental Response, Compensation, and Liability Act (42 USC 9601); Toxic Substances Control Act (15 USC 2601)	Yes, but mostly limited to particular sectors. Examples: NIST Special Publication 1270; NIST Special Publication 800-53; NIST Special Publication 800-37; OMB Guidance on AI; FDA Guidance for AI and Machine Learning in Medical Devices; SEC and FINRA Guidelines on AI in Financial Markets	No AI-specific federal regulator in the US; Federal Trade Commission, Federal Communications Commission, Equal Employment Opportunity Commission, Consumer Financial Protection Bureau and Department of Justice authority applies to "software and algorithmic processes, including AI." National Institute of Standards and Technology
BRAZIL	PL 2338/2023 is currently being discussed in the Senate, following public hearings, public consultation and the support of a Commission of Legal Practitioners	Brazilian Strategy for Artificial Intelligence (EBIA) launched in 2022	Yes, the protection of the environment and sustainable development is a principle in the proposed regulation. And AI agents must report to the competent authority the occurrence of serious security incidents, including severe damage to the environment	Brazilian Environmental Policy (6938/1981); Forest Code (12651/2012); National Policy on Climate Change (12187/2009); Biodiversity Law (13123/2015); National Solid Waste Policy (12305/2010); Environmental Crimes Law (9605/1998); National System of Conservation Units (SNUC) (9985/2000); New Sanitation Framework (14026/2020)	Yes. Examples: Norma ABNT NBR ISO/IEC 42001:2024; ABNT NBR ISO/IEC 38507:2023; ABNT NBR ISO/IEC 23894:2023; ABNT NBR ISO/IEC 22989:2023	The Federal government is expected to designate a competent authority, which will be the agency or entity of the Federal Public Administration responsible for implementing and overseeing Brazil's Proposed AI Regulation (new or existing).

ABNT = Associação Brasileira de Normas técnicas; ISO = International Organization for Standardization; PL = draft bill (*projeto de lei*); RFI = Request for Information
FDA = Food and Drug Administration; NIST = National Institute of Standards & Technology.
Source: created by the authors based on existing policies, guidelines and legislation.

FINAL REMARKS: ADDRESSING AI'S HIDDEN ENVIRONMENTAL AND SOCIAL COSTS TRANSNATIONALLY

As countries and jurisdictions regulate AI, including transnational perspectives about climate action and environmental justice is crucial. It is possible to reimagine a comprehensive regulatory ecosystem that includes hidden costs, especially for historically marginalized communities and global majority countries. Below are five preliminary considerations to move this process forward.

Transnational multistakeholder engagement: Connect discussions taking place within spaces like the UN Internet Governance Forum and COP, building bridges and opportunities for multistakeholder collaboration that includes the interests of the countries mostly affected by extreme weather and/or that have faced historical extraction of resources. The efforts should no longer be siloed.

Consider data infrastructure and embodied carbon: When considering environmental and social costs of AI, it is crucial to consider the resources that go into developing and training AI models. From the extraction of raw materials used in hardware to the disposal and recycling of outdated technologies, the AI lifecycle includes energy-intensive processes like data training and storage, which significantly contribute to carbon emissions. Furthermore, resources like cobalt, a critical component in the batteries that power AI hardware, have been linked to severe environmental degradation and human rights abuse, including child labor, hazardous working conditions, and the displacement of local communities.

Learn from other sectors and industries: Regulatory efforts in industries like medical, construction, and civil aviation offer valuable lessons for "big data ecologies" (Hogan, 2018), both in terms of best practices and mistakes to avoid. Existing tools and guidelines can help incorporate risk assessments, accountability mechanisms, and life cycle planning for technology, all grounded in a human rights-based approach that considers both big data and environmental justice.

Listen to people: Advocacy efforts and coalitions can play a big role in increasing awareness about the hidden environmental and social costs of AI. Meaningful community engagement is essential in this process, going beyond public hearings and online public consultations that, despite their importance, might not reach the communities most affected by harmful technologies. To build trust in technologies and governments, moving away from opaque concepts and into actual efforts to incorporate people's needs and perspectives is a good starting point.

Changes in higher education: Data science is growing as an interdisciplinary field, with more undergraduate and graduate programs offered in higher education (Academic Data Science Alliance, 2024). As universities invest in powerful computing and data centers, it is crucial to incorporate environmental and data justice into curricula (see data collected from syllabi in Appendix I). While other STEM fields, like Engineering and Computer Science, established ethical standards in the 1970s (Hoffmann & Cross, 2021), teaching data ethics remains challenging, and the environmental impact of AI is often ignored, with courses focusing more on AI's role in addressing environmental issues rather than its consequences.

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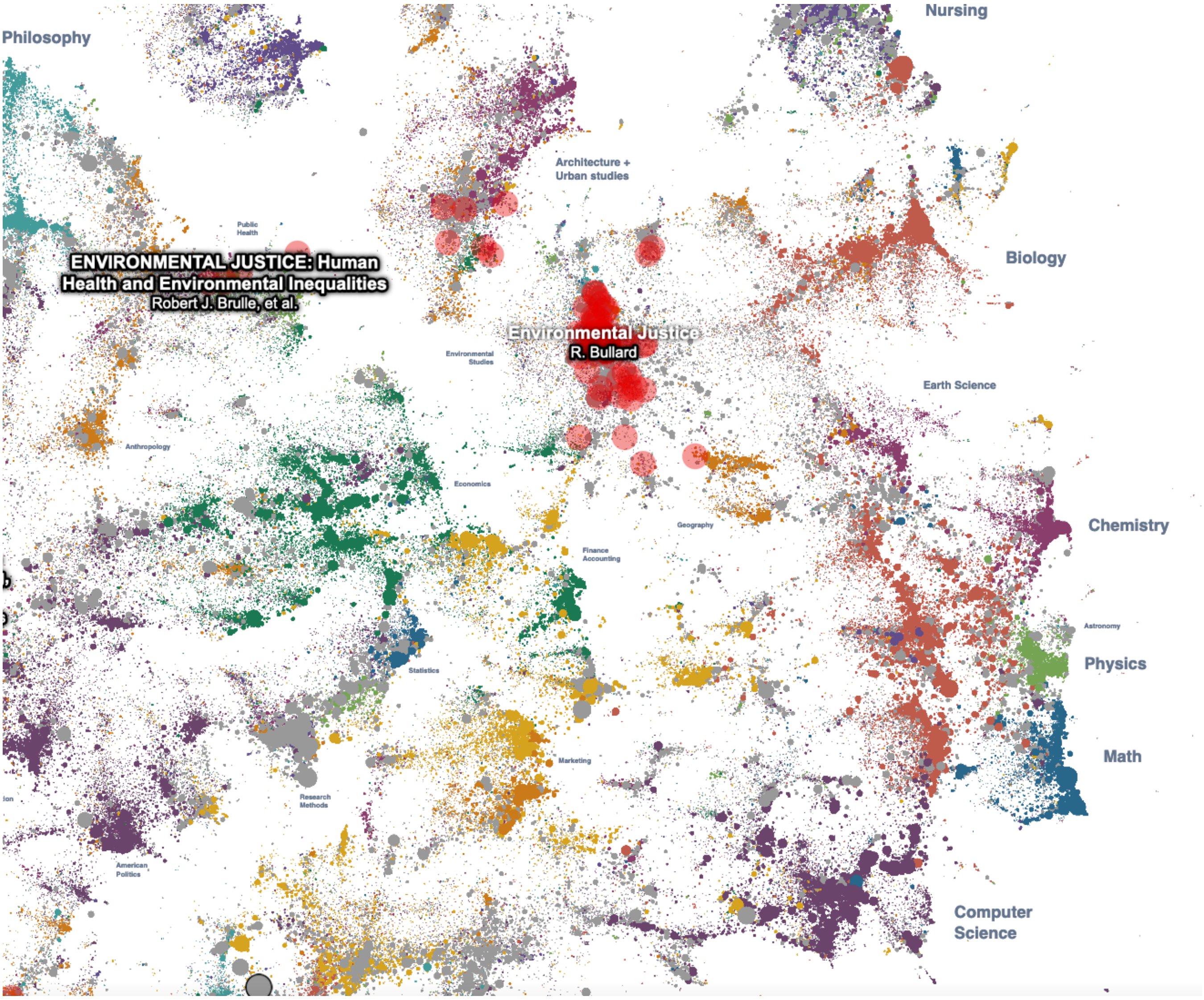
Appendix

The data in Fig. 1 represents the most frequently assigned texts in the Open Syllabus corpus, focusing on environmental justice citation. The graph is formed by connecting syllabi with the books and articles assigned in the course, with some areas overlapping or keeping distance. Environmental studies rarely converse with fields like computer science, indicating that students often do not have much contact with environmental studies and environmental justice scholarship.

Figure 7. Most frequently assigned texts in syllabi according to different disciplines, based on environmental justice citations.



Source: Open Syllabus Galaxy (https://galaxy.opensyllabus.org/)[181]

[181] More information: https://blog.opensyllabus.org/galaxy-v2